Quantitative analysis of self-organizing multiagent interaction with entropy and mutual information

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Abstract

In the research of a multiagent system, the indicators such as a task achievement ratio and a payoff have been used for analyzing a system. These indicators are important for the point that agents need to accomplish a task. However they are inadequate to make clear the entity of phenomena that occur in complex system, because they are specialized in the target system and the analysis is also specialized. In these respects the approaches that analyze a system quantitatively are begun to investigate in recent years. In our research, we propose the approach that analyzes a multiagent system quantitatively by focusing on the dynamics of a system and interaction among multiagents. We use two indicators, i.e., entropy and mutual information, for analyzing a system. Entropy estimates the behavior of an agent and mutual information estimates interactions between two agents. For verifying these propositions, we conduct verification experiment in the simple slime mold model. The result shows a relationship between agents' behavioral patterns and two indicators, therefore our approach using entropy and mutual information is available for analyzing a multiagent system.

Keywords. Multiagent system, Quantitative analysis, entropy, mutual information, interaction

1 Introduction

The researchers who construct multiagent systems must deal with the complex behavior of self-organization. Self-organization in multiagent systems emerges from agents' behavior, which is independently autonomous but corporately structured by interactions among agents and the environment. Researchers want to reveal these interactions because the coherence of the agents' local behavior and the system's overall behavior is required in designing systems.

Historically, researchers analyze system's overall behavior with the indicators such as a task achievement ratio and a payoff. These indicators are important for the point that agents need to accomplish a task. However they are inadequate to make clear the entity of complex systems and it is difficult to say why and how the task is achieved or how we get higher score. Since they are specialized in the target system and the analysis is also specialized. Therefore analyses that quantify the entity of systems universally are required. In these respects, there are researches that comprehend the dynamics of systems and agents with the concept of entropy [1], [2], [3], [4]. In these researches they consider about the behavioral diversity and the constraint with variance of entropy, and attempt to quantify the system.

In this paper, we propose the approach that analyzes a multiagent system quantitatively by focusing on the dynamics of a system and the interaction among multiagents as the entity of systems. In particular, we quantify the system's overall behavior and the intensity of interactions among agents and analyze systems.

2 Analysis of multiagent interaction

The interactions among multiagent in self-organization systems are considered to be interchange of information about the state of agent. The discussion of the relationship between these information and entropy is done historically [5]. In particular, decrease of entropy is great issue, and it is said that

- gain of information causes decrease of entropy and emerge constraint and
- gain of information constantly keeps up these constraint.

Therefore it is considered that information and entropy are important to capture the entity of multiagent interaction.

The concept of entropy is defined three contexts, i.e., thermodynamics, statistical mechanics and information theory; particularly information theory definition is called information entropy or Shannon's entropy [6]. Though informational definition does not inherit two other definitions, there are common entities because of the sameness of these formulas. With using information entropy, analysis of multiagent systems are studied in thermo dynamics perspective [1] and nonequilibrium thermodynamics perspective [2]. Therefore we use informational theoretical approach to quantify the entity of multiagent system.

Our analysis method uses two indicators entropy and mutual information, where mutual information is the indicator of the value of information. In our approach we can analyze

1. agent's behavior, e.g., stability, constraint or complexity with entropy and
2. the intensity of interactions between two agents with mutual information.

When one computes these indicators, what to observe as states is the great issue. Then consider about an agent, it is the autonomous individual that takes input from environment through its sensors and outputs through these input and decision-making process. At this time, agent's decision-making is followed its internal state, which can be variously designed. For capturing the essential states of agent that is not specialized in systems, agent's internal state depends systems and is not just as well. Whereat we use agent's input and output as the state of agent.

3 Experimental setup

We experiment with these concepts using a simple model of self-organization, slime mold model. In this section we describe the experiment in the slime mold model and how one measures entropy and mutual information.

3.1 Slime mold model

The group behavior of slime mold cells is the famous focus for models of self-organization [7]. Normally they move around as individual amoebas throughout their substrate, performing a simple random walk. But when the environmental situation worsens, they suddenly change their behavior and aggregate to a single multi-cellular body. During this aggregation process, they emit a chemical signal called cAMP to guide the collective movements. As they move, they follow the cAMP gradient in the environment.

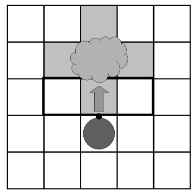

Figure 1: The environment of slime mold model

The whole process is a self-organization. Though all amoebas act with local information around them and without any other guidance such as coordinating the aggregation, they aggregate.

In the slime mold model, amoeba agents are placed on the grid world as Figure 1. An agent and environment model are described as follows.

Agent model

An agent acts as described below at each step.

1. Put cAMP on the current grid.
2. Sense the density of cAMP on the forward 3 grids in 8 neighbors.
3. Move to the grid that has the most cAMP.

Environment model

In the environment, cAMP is defined on the grid as parameters $T(x,y)$ and $P(x,y)$. $T(x,y)$ denotes the amount of cAMP on the grid (x,y), and $P(x,y)$ denotes the density of cAMP over the grid (x,y). An agent can sense the density of cAMP over the grid.

As time passes, cAMP evaporates and diffuses. By evaporation and diffusion, $T(x,y)$ and $P(x,y)$ changes into $T^*(x,y)$ and $P^*(x,y)$ at each step

$$T^*(x,y) = (1-\gamma_{eva})T(x,y) + \Delta T \tag{1}$$

$$\Delta T = \{ \begin{array}{cc} Q & \text{if an agent exists on grid } (x,y) \\ 0 & \text{otherwise} \end{array} \tag{2}$$

$$\begin{aligned} P^*(x,y) = P(x,y) + \gamma_{dif}\{P(x-1,y) + \\ P(x+1,y) + P(x,y-1) + P(x,y+1) \\ -5P(x,y)\} + \gamma_{eva}T(x,y) \end{aligned} \tag{3}$$

where Q denotes the amount of cAMP put by an agent in 1 step, and γ_{eva} and γ_{dif} denotes the evaporation rate and the diffusion rate of cAMP, which defines the property of cAMP.

3.2 The parameter of slime mold model

In the slime mold model, the cAMP's property that is defined by evaporation and diffusion rate affects the pattern of agents' self-organizational process. We compare these various patterns and the distribution of entropy and mutual information in our experiment, and verify our proposition.

The environment is 50×50 grid world, and contained 50 agents. We change cAMP's property to vary information's property among agents in respect of time length and accuracy, and the value of evaporation and diffusion rate is set to 4 different values, i.e.,

a. $\gamma_{eva} = 0.1$, $\gamma_{dif} = 0.1$

b. $\gamma_{eva} = 0.1$, $\gamma_{dif} = 0.3$

c. $\gamma_{eva} = 0.5$, $\gamma_{dif} = 0.1$

d. $\gamma_{eva} = 0.5$, $\gamma_{dif} = 0.3$.

We experiment with these setups at 1000 steps.

3.3 Measuring entropy and mutual information

Computing entropy and mutual information requires that we measure

1. the set of an agent X's states $x \in \{x_1, \cdots, x_n\}$ (i.e. input and output) and
2. the probability $p(x)$ of being those states,

where the agent's input is the discrete density of cAMP that exist on agent's forward 3 grids, and output is the agent's moving direction toward its facing direction.

Measuring those states is observation of the agent at each step. To measure the probability, we take Monte Carlo approach. By counting those states in whole step of 1 experiment, we estimate the probability.

With using these variables, entoropy of an agent X and mutual information among an agent X and Y is defined in following equations,

$$H(X) = -\sum_x p(x) \log p(x) \tag{4}$$

$$I(X:Y) = \sum_x \sum_y p(x,y) \log \frac{p(x,y)}{p(x)p(y)} \tag{5}$$

Table 1: The distribution of agents' entropy and mutual information in the slime mold model (in 100 trials)

	$\bar{I}$	$V(I)$	$\bar{H}$	$V(H)$	r_{Id}
a.	0.21	5.2×10^{-3}	0.53	1.5×10^{-2}	-0.31
b.	0.048	3.1×10^{-4}	0.34	4.5×10^{-3}	-0.41
c.	0.23	4.9×10^{-3}	0.54	1.1×10^{-2}	-0.34
d.	0.056	6.8×10^{-5}	0.39	3.3×10^{-4}	-0.11

4 Experimental results

Table 1 shows entropy and mutual information in each setup, a $\sim$ d, where $\bar{I}$ and $V(I)$ denote the average and variance of mutual information for randomly selected 100 pairs of agents. $\bar{H}$ and $V(H)$ denote the average and variance of entropy for all agents. r_{Id} denotes correlation coefficient between mutual information and Euclidean distance of pairs of agents. The results show that the average of mutual information is larger in the setting a and c than b and d, and it is considered that agents interact more intensive in the setting a and c. The average of agents' entropy is smaller in the setting b and d, and the states of agents will be stable.

On the other hand, we look the states of agents in visible by Figure 2 $\sim$ 5. In the setting a and c, many agents form clusters by self-organization. On the contrary many agents act independently in the setting b and d. These behavioral patterns are same as we see the difference of mutual information in each setup on the point of the intensity of interactions. Moreover, the value of r_{Id} shows tendency that the closer two agents are, the intensive they interact.

In addition, we look the process of forming cluster to look the stable of the system. In the setting a and c, because of the intensity of interactions, the agents form various cluster one after another in 1 experiment. While in the setting b and d, when the agents form a cluster, they seldom go out from this cluster and keep it up because the cAMP dropped by the agent out of them is weak and not enough to draw them in. These behavioral patterns are also same as the analysis by entropy, i.e., the states of agents are more stable in the setting b and d than a and c.

5 Summary

In this paper, we proposed the quantitative analysis of multiagent interaction with entropy and mutual

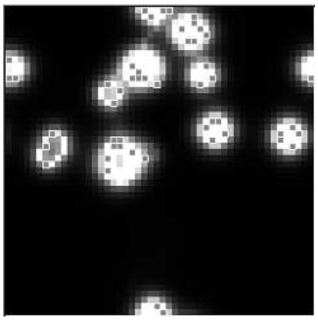

Figure 2: The look of the system at 1000 step in the setting a. The agents form some clusters.

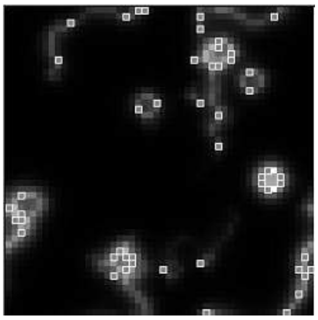

Figure 3: The look of the system at 1000 step in the setting b. The agents form small clusters, and some agents act independently.

Figure 4: The look of the system at 1000 step in the setting c. The agents form big cluster.

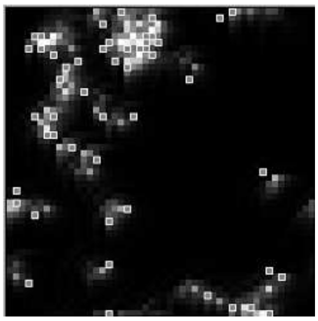

Figure 5: The look of the system at 1000 step in the setting d. Many agents act independently.

information. We conducted verification experiment in the slime mold model to quantify the interactions in self-organizational process. The results show the relationship between agents' behavioral patterns and our analysis, and validity of our proposal method.

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